CS630 Representing and Accessing Digital Information

Part-of-Speech Tagging

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Based on slides from Prof. Claire Cardie

Why is POS Tagging Hard?

- **Ambiguity**
  - He will race/VB the car.
  - When will the race/NOUN end?
  - The boat floated/VBD down the river.
  - The boat floated/VBN down the river sank.
- **Average of ~2 parts of speech for each word**
- **The number of tags used by different systems varies a lot. Some systems use < 20 tags, while others use > 400.**

Part-of-Speech Tagging

- **Task definition**
  - Part-of-speech tags
  - Task specification
  - Why is POS tagging difficult
- **Methods**
  - Transformation-based learning approach [Brill 93]
  - Hidden Markov Models

Among Easiest of NLP Problems

- **State of the art methods achieve ~97% accuracy.**
- **Simple heuristics can go a long way.**
  - ~90% accuracy just by choosing the most frequent tag for a word
- **But defining the rules for special cases can be time-consuming, difficult, and prone to errors and omissions**

Part-of-Speech Tagging Task

- **Assign the correct part of speech (word class) to each word in a document**

  "The/DT planet/NN Jupiter/NNP and/CC its/PRP moons/NNS are/VBP in/IN effect/NN a/DT mini-solar/JJ system/NN ,/, and/CC Jupiter/NNP itself/PRP is/VBZ often/RB called/VBN a/DT star/NN that/IN never/RB caught/VBN fire/NN ./."
- **Needed as an initial processing step for a number of language technology applications**
  - Information extraction
  - Answer extraction in QA
  - Base step in identifying syntactic phrases for IR systems
  - Critical for word-sense disambiguation (WordNet apps)
  - …

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Transformation-Based Learning

- **Machine learning technique**
  - For acquiring simple default heuristics and rules for special cases
  - Rules are learned by iteratively collecting errors and generating rules to correct them.
- **Requires a large (training) corpus of manually tagged text**

Transformation-Based Learning

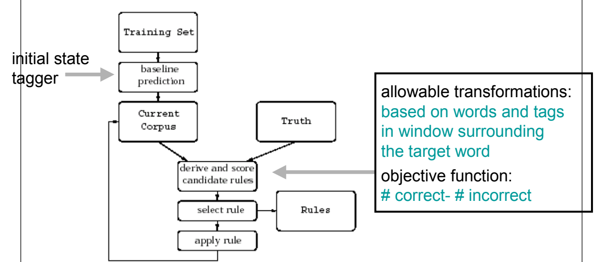
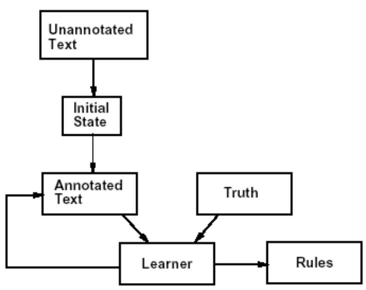


Figure 1: Transformation-based Learning

[Brill 1993]

TBL: Top-Level Algorithm



Learns an ordered list of transformations (i.e. rewrite rules)

Learning Algorithm: Greedy Search

- **Specify**
  - An initial state annotator
  - Space of allowable transformations
  - Objective function for comparing corpus to truth
- **Algorithm**
  - Iterate
    - Try each possible transformation
    - Choose the one with the best score
    - Add to list of transformations
    - Update the training corpus
  - Until no transformation improves performance

Rewrite Rules

- **Rule**
  - Change *modal* to *noun*, if preceding word is a *determiner,*
- **Example**
  - Determiner: the, a, an, this, that …
  - Modals: can, will, would, may, might…followed by the main verb
  - The/*det* can/*modal* rusted/*verb* ./.
  - The/*det* can/*noun* rusted/*verb* ./.

Transformation Templates

- **Change tag A to B when:**
  - preceding/following word is tagged Z
  - word two before/after is tagged Z
  - one of the two preceding/following words is tagged Z
  - one of the three preceding/following words is tagged Z
  - preceding word is tagged Z and following word is tagged W
  - preceding/following word is tagged Z and word two before/after is tagged W

Generating Transformations

- Apply the initial tagger and compile types of tagging errors. Each type of error is of the form:
  - <incorrect tag, desired tag ,# of occurrences>
- For each error type, instantiate all templates to generate candidate transformations.
- Apply each candidate transformation to the corpus and count the number of corrections and errors that it produces. Save the transformation that yields the greatest improvement.
- Stop when no transformation can reduce the error rate by a predetermined threshold.

Tagging New Text

- **The resulting tagger consists of two phases:**
  - Use the initial tagger to tag all the text
  - Apply each transformation, in order, to the corpus to correct some of the errors.
- **The order of the transformations is very important!**
  - For example, it is possible for a word's tag to change several times as different transformations are applied. In fact, a word's tag could thrash back and forth between the same two tags.

Example

- Suppose that the initial tagger mistags 159 words as verbs when they should have been nouns.
- Produces the error triple:

  < *verb, noun,* 159>
- Suppose template #3 is instantiated as the rule:

  Change the tag from verb to noun if one of the two preceding words is tagged as a determiner.
- When this template is applied to the corpus, it corrects 98 of the 159 errors. But it also creates 18 new errors. Error reduction is 98-18=80.

Evaluation

- **Training: 600,000 words from the Penn Treebank WSJ corpus**
- **Testing: separate 150,000 words from PTB**
- **Assumes all possible tags for all test set words are known.**
- **97.0% accuracy**
- **Tagger learned 378 rules.**

Learned Rules

1. **NN→VB if the previous tag is TO**

   I wanted to/TO win/NN→VB a Subaru WRX…
2. **VBP→VB if one of the prev-3 tags is MD**

   The food might/MD vanish/VBP→VB from sight.
3. **NN→VB if one of prev-2 tags is MD**

   I might/MD not reply/NN→VB
4. **VB→NN if one of the prev-2 tags is DT**
5. **VBD→VBN if one of the prev-3 tags is VBZ**
6. **VBN→VBD if one of the previous tag is PRP**

Problems?

- **Not lexicalized**
  - Transformations are entirely tag-based; no specific words were used in the rules.
  - But certain phrases and lexicalized expressions can yield idiosyncratic tag sequences, so allowing the rules to look for specific words should help…
  - Add additional templates
    - E.g. when the preceding/following word is *w*...
  - Tagger achieves 97.2% accuracy
    - First 200 rules achieved 97.0%
    - First 100 rules achieved 96.8%
  - Learns 447 rules
- **Unknown words**

Transformation-Based Learning

- **Part-of-speech tagging**
  [Brill 1995; Ramshaw & Marcus 1994]
- **Prepositional phrase attachment**
  [Brill & Resnik 1995]
- **Syntactic parsing**
  [Brill 1994]
- **Noun phrase chunking**
  [Ramshaw & Marcus 1995, 1999]
- **Context-sensitive spelling correction**
  [Mangu & Brill 1997]
- **Dialogue act tagging**
  [Samuel et al. 1998]

States and Transitions

- **States**
  - Think about as nodes of a graph
  - One for each POS tag
  - special start state (and maybe end state)
- **Transitions**
  - Think about as directed edges in a graph
  - Edges have transition probabilities
- **Output**
  - Each state also produces a word of the sequence
  - Sentence is generated by a walk through the graph

Part-of-Speech Tagging

- **Part-of-Speech Tagging**
  - Part-of-speech tags
  - Task specification
  - Why is POS tagging difficult
- **Methods**
  - Transformation-based learning approach [Brill 93]
  - Hidden Markov Models
- **Named Entity Recognition**

Probabilistic Model

- **Starting state s_0**
  - Specifies where the sequence starts
- **Transition probability $P(S_t|S_{t-1})$**
  - Probability that one states succeeds another
  - Matrix of size #states * #states
- **Emission probability $P(W_t|S_t)$**
  - Probability that word is generated in this state
  - Matrix of size #states * #words

=> Every word + state sequence has a probability P(W,S)

$$P(w_1,\ldots,w_n,s_{start},s_1,\ldots,s_n)=\left[\prod_{i=1}^{n}P(w_i\mid s_i)P(s_i\mid s_{i-1})\right]$$

Hidden Markov Models

- **Application to POS tagging:**
  - View POS tagging as a sequence of word classification tasks
  - Goal: Train an HMM to label every word with one of the POS tags.
- **What is a HMM?**
  - Hidden Markov Model (HMM) represents a process of generating the word and tag sequence
  - Probabilistic model
  - Probability for each word and tag sequence
  - Predict most likely tag sequence for a given word sequence

HMM Inference Type I: Evaluation

- **Question: What is the probabiliy of an output sequence given an HMM**
  - Given fully specified HMM: s_0, $P(W_t|S_t)$, $P(S_t|S_{t-1})$
  - Find for a given $w_1,\ldots,w_n$

$$P(w_1,\ldots,w_n)=\sum_{(s_0,\ldots,s_n)}\left[\prod_{i=1}^{n}P(w_i\mid s_i)P(s_i\mid s_{i-1})\right]$$

  - Naïve algorithm exponential runtime; “forward” algorithm linear in length of sequence
  - Language model
  - Example: classify sequences as question vs. answer sentence.

HMM Inference Type II: Decoding

- **Question: What is the most likely state sequence given an output sequence**
  - Given fully specified HMM: s_0, $P(W_t|S_t)$, $P(S_t|S_{t-1})$
  - Find

$$\max P(s_1,\ldots,s_n \mid s_0, w_1,\ldots,w_n) = \max_{(s_1,\ldots,s_n)}\left[\prod_{i=1}^{n} P(w_i \mid s_i) P(s_i \mid s_{i-1})\right]$$

  - "Viterbi" algorithm has runtime linear in length of sequence
  - Example: find the most likely tag sequence for a given sequence of words

Estimating the Probabilities

- **Given: Fully observed data**
  - Pairs of word sequence with their state sequence
- **Estimating transition probabilities $P(S_t|S_{t-1})$**

$$P(s_a \mid s_b) = \frac{\#ofTimesStateAFollowsStateB}{\#ofTimesStateBOccurs}$$

- **Estimating mission probabilities $P(W_t|S_t)$**

$$P(w_a \mid s_b) = \frac{\#ofTimesWordAIsObservedInStateB}{\#ofTimesStateBOccurs}$$

- **Smoothing the estimates**
  - Laplace smoothing -> uniform prior
  - See naïve Bayes for text classification
- **Partially observed data: Expectation Maximization (EM)**

HMM's for POS Tagging

- **Design HMM structure (vanilla)**
  - States: one state per POS tag
  - Transitions: fully connected
  - Emissions: all words observed in training corpus
- **Estimate probabilities**
  - Use corpus, e.g. Treebank
  - Smoothing
  - Unseen words?
- **Tagging new sentences**
  - Use Viterbi to find most likely tag sequence

Experimental Results

Tagger	Accuracy	Training time	Prediction time
HMM	96.80%	20 sec	18.000 words/s
TBL	96.47%	9 days	750 words/s

- **Experiment setup**
  - WSJ Corpus
  - Trigram HMM model
  - Lexicalized
  - from [Pla and Molina, 2001]